Detecting sleep deprivation in working environments

Using machine learning algorithms

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> introduction

Sleep deprivation in high-stress work environments can compromise safety, cause health issues, and negatively impact the work being done. Our research focuses on the detection and analysis of sleep deprivation to foster safer and more efficient work environments. We are using machine learning to develop a pipeline to identify if an individual is in a sleep-impaired state from their physiological data.

In the past, eye and face tracking, heart rate, electrodermal activity (EDA), motion, and voice recordings have all been used to identify sleep deprivation. We aim to further optimize the accuracy of our prediction model by using multiple types of data such as heart rate, EDA, and potentially motion tracking. While shown to be effective, we had concerns that eye and face tracking or voice recording would be difficult to carry out in an active or loud environment, so we focused on other data types.

> methods

Currently, we are in the process of preliminary data collection and analysis to better understand the data and figure out how to analyze it.

To do this, a researcher collected heart rate, EDA, and motion data on themself using the Empatica E4 sensor, which is worn as a wristband.

Three hours of data were collected, each preceded by a 6 minute long Psychomotor Vigilance Task (PVT), which has been proven to be effective in detecting sleep deprivation. While collecting data, the researcher took different variations of the same 1-hour practice examination requiring high cognition.

Data was collected on three different days in the same location, in a temperature controlled environment. No steps were taken to induce sleep deprivation beyond its natural occurrence.

> future work

More data is necessary to train an accurate prediction model, including a wider range of sleep states and participants. Past studies have used Convolutional Neural Networks, Time Batched Long Short-Term Memory (TB-LSTM) networks, Recurrent Neural Networks, Linear Discriminant classification models, Naive Bayes classifiers, and Random Forest classifiers to model similar problems. As we move forward, we can also experiment with different models and determine the best to apply to this challenge.

> sources

Icons from www.flaticon.com

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PVT: https://luketurner.org/PersonalPVT/#/

> data collected

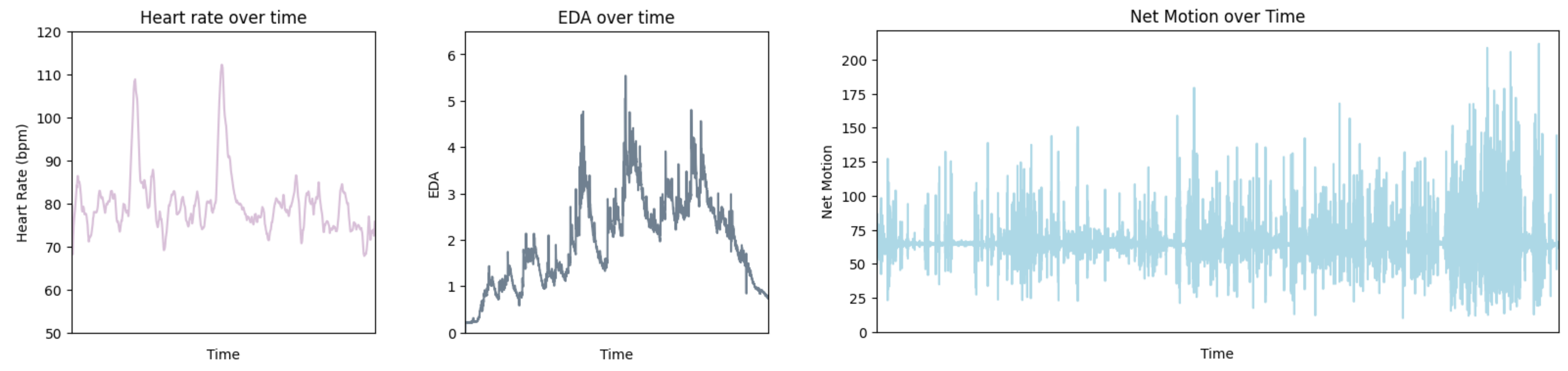
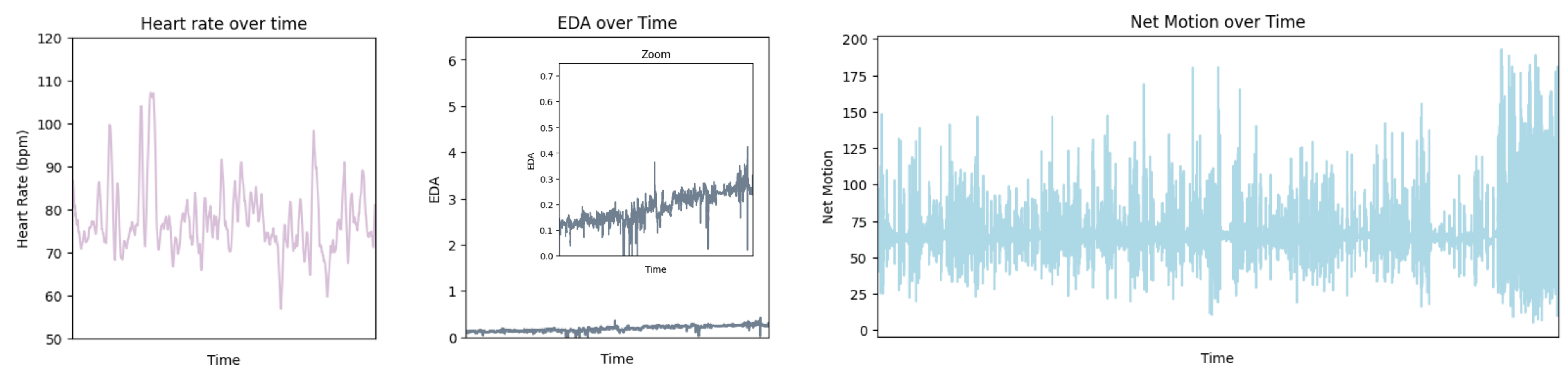


Fig 1. To the right are graphs of the heart rate, EDA, and net motion (derived from x, y and z accelerometer data) over the period of an hour in a sleep deprived state. In these graphs, the researcher attained a very low score PVT of 56.5%.

Fig 2. To the left are graphs of the heart rate, EDA, and net motion (derived from x, y and z accelerometer data) over the period of an hour in a well rested state. In these graphs, the researcher attained a PVT score of 86.6%.



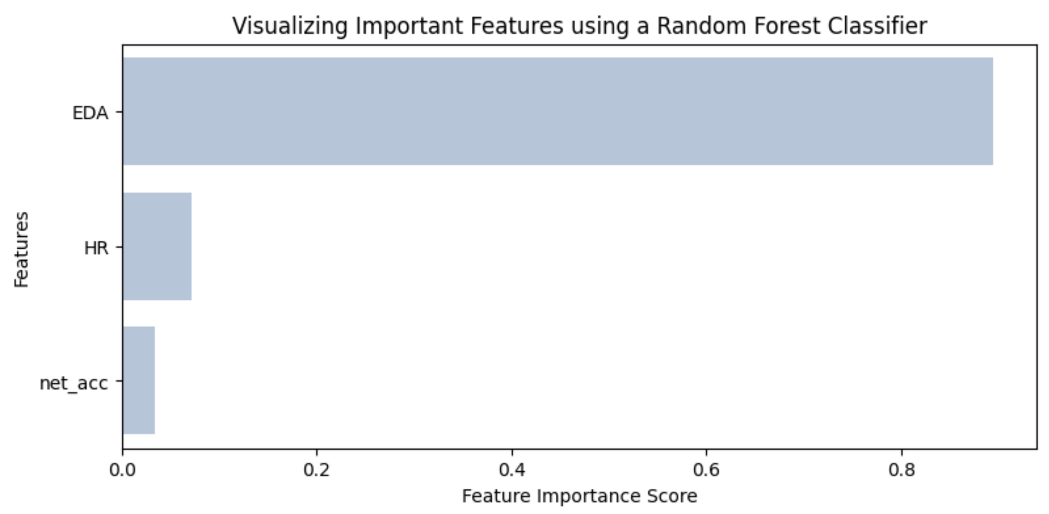
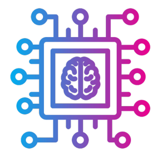


Fig 3. Feature analysis after fitting the data to a random forest classifier seems to suggest that electrodermal activity is the best predictor of sleep deprivation. However, given the small size of the dataset, this may not be accurate for all data.

> data analysis

While a simple threshold could identify raised electrodermal activity (a sign of a sleep deprivation), EDA can be elevated for many reasons, including normal physical activity or temperature increase. Machine learning algorithms can identify patterns in complex data with nonlinear relationships.



To solve this problem, we can create a model which takes as input the e4 data and classifies this data as either normal or sleep deprived.

To do this, we will ‘show’ the model thousands of e4 data points. During training, the model will attempt to predict whether the performance is sleep deprived, and the model will be adjusted based on the accuracy of its prediction.

Accuracy on test set for Random Forest Classifier on preliminary dataset:

0.9882

However, this high accuracy can in part be attributed to the small dataset and the fact that data was only collected on one person performing one specific task.